COMSATS University Islamabad, Lahore Campus

Project Registration

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Subject: Advanced Topics in Computer Vision **Date:** May 20, 2021.

Project/Paper Title: Deep Residual Learning for Detecting Fire and Smoke

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Deep Residual Learning for Detecting Fire and Smoke

Abstract:

Fire and Smoke is a huge problem related to safety issue. Heat and Smoke detectors are unable to control this problem completely. These days Artificial Intelligence is taking over the world so our aim is to introduce a model using Artificial Intelligence which will be better choice to tackle fire and smoke problem rather than heat sensors. In this paper we present a deep residual network on Fire and smoke data set using transfer learning. We prefer to use deep Residual network because it will perform better as compared to previous methods. In this paper we performed experiment using fire and smoke dataset on Resnet50 and VGG19. Using Resnet50, we got 93 percent accuracy and using VGG19, we got 85 percent accuracy which proves that residual network is better than other deep learning networks. We also discussed some drawbacks of heat sensors and advantages of our deep residual trained model.

Introduction:

Heat and Smoke detectors are used to protect people and property by generating an alarm when fire occurs. Due to some limitations heat and smoke detectors are unable to perform and sometimes generate false alarms. There are some drawbacks of using smoke and heat detectors. Some of them mentioned below:

- Very sensitive, which can lead to false alarms as a product of cooking.
- Not as responsive to smoldering fires - they are minutes slower than photoelectric sensors in detecting smoke particles from smoldering fires.
- Use of radioactive material is a concern.
- The chamber entrances of smoke and heat detectors are big enough to fit a small insect. Insects can set off alarm by interfering with the sensors.
- A buildup of dust can also affect your smoke alarm.

In this Artificial Intelligence era, we thought to present a model which can handle fire and smoke detection problem more accurately. We trained our model using deep learning which is a very promising area of Artificial Intelligence. In deep learning, there are a lot of networks present to train a model, but we choose the concept of Residual Network with transfer learning for our model. We did not choose other network i.e., VGG-Net, Plain Network or Shallow Network for our model because residual network performance is better than other deep neural networks. Some benefits of our trained model are:

- Many heat sensors can be replaced by a single camera.
- Heat sensor may malfunction and give false alarm, but a well-trained deep learning model can avoid such incidents.
- Our trained model will use a single camera to watch the current scenarios and if any smoke or heat occurs in the scene it will accurately generate the alert.

Related Work:

There are some works has been done to solve fire and smoke detection problem using Artificial Intelligence. Here we discussed some of the related work:

Olayemi and Moses implemented Resnet method proposed by Kaiming H. et al [1] in python programming language and achieved 85 percent accuracy on fire and smoke data set [6]. Li-Wei Kang. et al [2] proposed image-based fire detection framework based on deep learning. They used YOLO (You look only once) deep model and achieved 99.38% accuracy on furg-fire-dataset. Mohit Dua et al [3] proposed fire detection model using Deep CNN instead of traditional CNN. They used VGG16 and MobileNet model with transfer learning on ImageNet data set and compared with traditional CNN. They observed that Deep CNN model with transfer learning performs more better than the traditional CNN. Another method proposed by Dongqing Shen. et al [4] for detection of flames using deep learning. They used YOLO (You Look Only Once) model and Shallow neural network. They achieved higher accuracy of their model using YOLO as compared to Shallow Neural Network. Another interesting method was given by Chuanchen Li and Yong Bai [5] for flame detection. They proposed two approaches to fasten the learning process and improve the detection performance based on transfer learning in this paper. First approach is by using and fine-tuning the existing transfer learning models. The other proposed approach is to use multiple transfer learning models to extract the image features. They achieved very high accuracy by using these two approaches.

Methodology:

Here we explain the working of our model:

1. **Dataset:** The dataset we choose to train our model is "Fire and Smoke Data Set" [6] which is uploaded on GitHub. This data set contains total 3000 images and it is divided into 3 classes fire, smoke, and normal scenes. For each class we use 900 images for training of our model and 100 images for testing of our model. We resize all images to [224,224].

2. **Methodology:** The methodology we choose to train our model is deep learning; and in deep learning, we choose Residual Network. We did not choose other deep neural network methods because of the degradation problem in those networks. Resnet was proposed by Kaiming H. et al [1], a team of Microsoft in 2015. ResNet is based on the concept of shortcut connections. It means skipping one layer. Shortcut connection simply perform identity mapping and their output is added to the above stacked layer resulting in use of lower number of parameters compared to other deep learning networks. That is why ResNet outperforms all other previous networks. In this paper we experimented on VGG19 and Resnet50 and we will see later in paper that ResNet50 is deeper model than VGG19, but its performance is better than VGG19. Moreover, we used transfer learning to train both models (ResNet50 and VGG19) with ImageNet weights.

3. **Experimental Result:** The proposed method was implemented in python programming language with Keras on personal computer. To train our model we imported pre-trained ResNet50 model from Keras in which hidden layer has already learned that is why we use transfer learning to freeze already learned layer and modified only trained input and output layer according to our own problem. For

activation function we used SoftMax activation because prediction value is for multiple classification. For optimizing weights, we used the Adam optimizer. We tested our proposed model on 300 images which is divided into 3 classes. Our proposed network model contains total 23,888,771 parameters from which 301,059 parameters are trainable and 23,587,712 parameters are non-trainable. We run our code at 10 Epochs (per epoch 85 steps) which specifies that it goes through training images 10 times and each time an update will made. After applying our experiment on ResNet50 model, we achieved 93 percent accuracy on our model. *Table 1* shows sample result of ResNet Model.

Table 1: Resnet 50 Sample Model

Epoch	Steps	Loss	Accuracy	Val_loss	Val_acc
1	85	2.4519	0.8578	2.5335	0.8767
7	85	1.3974	0.9500	4.1077	0.9133
10	85	1.3590	0.9574	2.6389	0.9333

Figure 1 and *Figure 2* shows the loss and accuracy graph of our ResNet50 model.

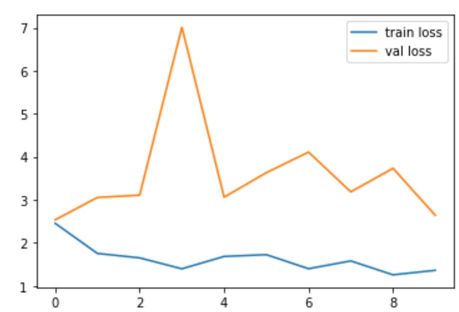

Figure 1: Resnet [50] loss

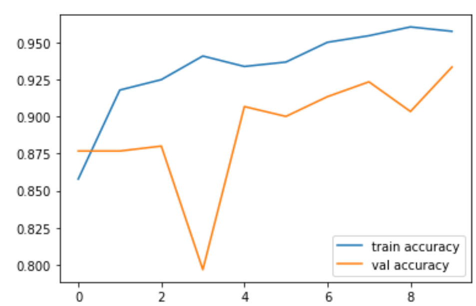

Figure 2: Resnet [50] Accuracy

VGG 19:

We performed this same experiment using the same data set on VGG19 model. VGG19 model contains total 20,099,651 parameters from which 75,267 parameters are trainable and 20,024,384 parameters are non-trainable. We trained the model at 10 Epochs, and it achieved 85 percent accuracy.

From the above experiments, it can be seen that Resnet50 model was deeper than VGG19 (50 layers vs. 19 layers) and still we got higher accuracy on ResNet50. *Table 2* gives sample result of VGG19 Model.

Table 2: VGG [19] Model Result

Epoch	Steps	Loss	Accuracy	Val_loss	Val_acc
1	85	3.3570	0.8374	3.6982	0.8233
7	85	2.3323	0.9348	8.2920	0.8433
10	85	2.2058	0.9370	7.4883	0.8567

Figure 3 and Figure 4 shows the graph of loss and accuracy of VGG19 model that we achieved.

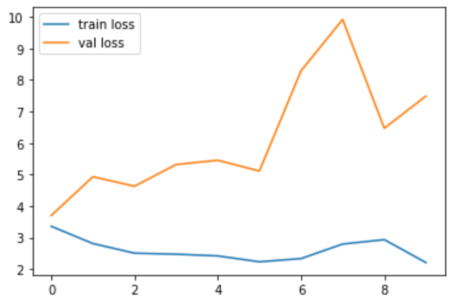

Figure 3: VGG [19] loss

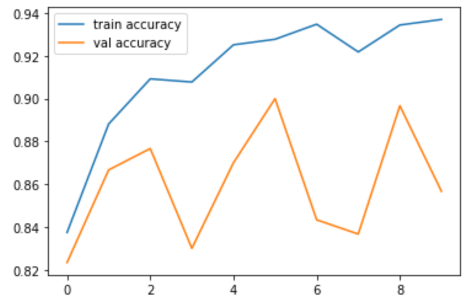

Figure 4: VGG [19] Accuracy

Conclusion:

Method	Accuracy
VGG [16]	0.8567
Resnet [50]	0.9333

The aim of this paper was to prove that Residual Networks perform better on Fire and Smoke data set [6] than other Deep Neural Networks. And we prove this point by experimenting on ResNet50 and VGG19. ResNet50 achieved 93 percent accuracy while VGG19 achieved 85 percent accuracy. This means that Residual Network will prove to be efficient to tackle fire and smoke detection and any other deep learning or Image Processing problem than other Deep Neural Networks.

References:

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[3]. M. Dua, M. Kumar, G. Singh Charan and P. Sagar Ravi, "An Improved Approach for Fire Detection using Deep Learning Models," 2020 International Conference on Industry 4.0 Technology (I4Tech), 2020, pp. 171-175, doi: 10.1109/I4Tech48345.2020.9102697.

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[6]. https://github.com/DeepQuestAI/Fire-Smoke-Dataset